Evaluating the Causal Effects of the Amazon Future Engineer Scholarship Program

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1. Introduction

High schools and colleges across the country increasingly offer courses in computer science and engineering, but first-generation students, low-income students, and students from historically underrepresented communities are much less likely to pursue and complete degrees in these fields. This disparity in choice of college majors has been linked to differences in prior academic preparation, and has in turn left its mark on the composition of America's workforce (Arcidiacono et al., 2012; Thompson, 2021; Tran et al., 2023).

This document reports findings from an evaluation of the Amazon Future Engineer Scholarship Program (AFE), an initiative designed to encourage students to explore computer science and expose them to related career opportunities. While mounting evidence suggests that financial aid can boost rates of college enrollment and degree attainment, less is known about whether and how scholarship programs can help students succeed in academically demanding majors with high earnings potential (Alon, 2011; Angrist et al., 2022; Brand & Xie, 2010; Deming & Dynarski, 2010; Goldrick-Rab et al., 2016). The AFE scholarship program provides generous renewable awards of up to $40,000 over four years to high school seniors intending to major in computer science (CS) or allied engineering fields in college. Unlike traditional scholarship programs, the AFE scholarship also provides career-oriented support to give students experience in computer science, including a summer internship opportunity at Amazon. This combination of financial and career-oriented support makes the AFE scholarship an interesting model to study for increasing engagement and diversity in the STEM workforce.

To assess the impact of the AFE program, we link scholarship application data from the 2020-2023 enrollment cycles to a combination of administrative and survey data on student outcomes. We obtained historical AFE application records from Scholarship America, a non-profit organization that has administrated the AFE program since 2019.[1] For college enrollment and degree

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[1] Scholarship America is the largest non-profit distributor of private scholarships in the U.S. Founded in 1958, Scholarship America's corporate and non-profit partners award more than $275 million in scholarship awards each

attainment data, we turned to the National Student Clearinghouse, which tracks students' choice of schools and majors. Besides measuring the aggregate effects of awards, we assess what groups of students are likely to benefit most from scholarship aid. To understand how AFE awards shape student outcomes, we surveyed past AFE applicants. This survey elicited additional information on students' financial aid packages, campus experiences, and career plans.

AFE recipients are selected on a range of need- and merit-based criteria, complicating the task of identifying the causal impacts of awards. Students with exceptional grades, essays, or letters of recommendation may be likely to succeed in college even in the absence of aid. To isolate the impact of the AFE program, we adopt a research design based on the mechanism Scholarship America uses to select award winners. Scholarship America staff assign numerical scores to applications according to predetermined review criteria. In each application cycle, students with the best application scores are awarded scholarships until no awards remain. Because the qualification threshold is unknown to applicants beforehand, whether an applicant falls just above or below the cutoff score is determined primarily by chance. This allows for a regression discontinuity design (RDD) that reveals the causal effects of awards by comparing the outcomes of students just above and just below the cutoff score.

Using this RDD approach, we find that AFE awards significantly increase the total scholarship aid received by students, while decreasing their loan burden. Further, awards reduce the pressure on students to find jobs to support themselves in school, lowering the likelihood of work by 28 percentage points. We also find that AFE participants are more likely to report that that they have completed or plan to pursue an internship related to their studies, an effect likely driven by the AFE program's offer of a paid Amazon internship. Overall, the AFE program appears to shift students from work obligations during the school year toward summer internship opportunities with greater potential for career advancement.

Because most of the students in our study sample are relatively early in their college careers, we have only limited insight into the program's effects on their persistence in computer science and their career choices. Most institutions do not require or even encourage students to declare majors in their first years. However, we do find that AFE recipients are more likely to say that they intend to pursue a CS-related degree. A large proportion of students who complete an AFE internship at Amazon receive job offers from the company, which suggests one way that the program helps bolster the CS workforce. We hope to revisit these longer-run outcomes in future years as more of the study sample approaches graduation.

Our study was conducted through a research collaboration between Blueprint Labs, based at MIT, and Scholarship America, made possible with funding from Amazon. Blueprint Labs has contributed to the growing academic literature on scholarships and financial aid. In a long-term partnership with the Susan Thompson Buffett Foundation, Blueprint researchers randomized generous scholarships to public school students in Nebraska, finding that awards led to significant gains in degree attainment, particularly for low-income and first-generation students (Angrist et al., 2022). The results from this prior study corroborate our finding that scholarship awards have larger impacts for students belonging to groups that have not traditionally benefited from merit-based aid.

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year.

2. Literature

Many prior studies estimate the effects of financial aid on post-secondary attendance, persistence, and completion. Several prominent studies of state-funded aid programs have found large effects on both attendance and bachelor's degree completion (Castleman & Long, 2016; Cornwell et al., 2006; Dynarksi, 2000). Dynarski and Scott-Clayton (2013) survey quasi-experimental evidence from a range of state and federal aid programs, concluding that an additional $1,000 of grant aid leads to an average increase in college enrollment of 4 percentage points.

Comparatively little work focuses on the large number of private and employer-sponsored scholarship programs. Using an RDD, Page et al. (2019) find that the Dell Scholars Program had substantial effects on bachelor's degree completion, but no effects on initial college enrollment. In one of the few experimental evaluations of financial aid, Goldrick-Rab et al. (2016) find that the Wisconsin Scholars Grant has positive but small effects on degree completion for students already enrolled in college. Harris and Mills (2021) conduct a randomized evaluation of aid designed to cover the costs of attending two-year colleges for high school students in Milwaukee, finding modest substitution from four-year to two-year colleges. In prior work led by Blueprint Labs, Angrist et al. (2022) evaluate generous scholarships distributed by the Buffett Foundation to Nebraska high school seniors: Randomly awarded scholarships averaging $8,200 in the first year increased enrollment at four-year schools by 11 percentage points and bachelor's degree completion by 8 points.

In summary, the weight of evidence points to positive and significant effects of financial aid on both enrollment and degree completion. In many studies, estimated effects are larger for lower-income and first-generation students, suggesting that these groups may be especially likely to benefit from scholarship aid (Alon, 2011; Angrist et al., 2022; Bettinger et al., 2019; Brand & Xie, 2010; Goldrick-Rab et al., 2016). One explanation is that low-income students face credit constraints that prevent them from borrowing at the same rates as more wealthy students. As a result, more low-income students may be on the borderline of college attendance, making them more responsive to net price (Goldrick-Rab et al., 2009).

For students who would attend college even without aid, scholarship awards provide financial support that may help them weather challenges that could delay or otherwise impede their academic progress. Previous research suggests that scholarship aid plays a key role in reducing the burden of loans and work-study requirements, allowing students to focus more on academic work (Bozick, 2007; DesJardins & McCall, 2007). Aid may also induce students to live on campus and participate in extracurricular activities, strengthening their social ties while in school (Goldrick-Rab et al., 2009). The available evidence on the longer-run effects of financial aid and college on labor market earnings is relatively thin, though studies with access to administrative data on earnings generally find positive effects (Andrews et al., 2020; Bettinger et al., 2019; Zimmerman, 2014).

This project builds on existing evidence by evaluating the effects of a prominent private scholarship program on student outcomes. We use a credible quasi-experimental design to isolate causal effects, an approach made possible by linking administrative application and enrollment records. Most importantly, the unique design of the AFE scholarship allows us to assess the impact of an aid program that also provides extensive career support, including an internship opportunity. Combining administrative records and student surveys enables us to measure the program's impact on college students' career expectations and their engagement with professional opportunities, important but understudied mediators of downstream effects on degree completion and earnings.

3. The AFE scholarship program

3.1. *Program components*

Amazon Future Engineer Scholarship recipients receive up to $40,000 over four years to pursue a computer science or engineering degree at a U.S. college or university of their choice (the maximum award is $10,000 each year, not to exceed the student's unmet need). The number of awards ranged from 100 in the 2020 application cycle to 400 in the 2023 application cycle. Eligible scholars receive a paid internship offer at Amazon after their freshman year of college to gain practical work experience. Interns receive weekly one-to-one mentoring with designated Amazon employees, and they are connected with past AFE scholarship recipients, both in-person and virtually.

In addition to the internship, awardees receive extensive support during the school year, including access a fund to help cover the cost of financial emergencies. They also can obtain year-round mental health services from a non-profit partner, TBH, as well as leadership development and cohort community building from the Posse Foundation. This array of non-financial resources and opportunities is designed to help students gain an early footing in the academic community at their school; hone skills and receive mentorship outside the classroom; and weather unexpected challenges that may derail their academic progress.

3.2. *Selection and eligibility criteria*

To be eligible for the AFE scholarship, candidates must be high school seniors at the time of application, possess U.S. citizenship, and declare an intent to obtain a four-year degree in computer science or a related field.[2] Applicants must also have completed at least one high-school or college course related to computer science, engineering, or robotics. Until 2023, a minimum GPA of 3.0 was required, but that was relaxed to a GPA of 2.3 in the most recent cycle.

Scholarship America assigns each component of the AFE scholarship application—including essays and recommendations—a numerical rating according to predetermined criteria. These component scores are then combined into a single composite score. Roughly one-third of the composite score comprises academic factors, including GPA, standardized test scores, and class rank. Another third of the score is based on financial need. The final third reflects other attributes of the applicant, including extracurricular activities, essays, and letters of recommendation.

4. Data and samples

4.1. *Data sources*

We draw on three main data sources to evaluate the AFE scholarship program. The starting point is applicant-level data from Scholarship America submitted by students in the 2020 through 2023

[2] Qualifying fields include computer science, software engineering, computer engineering, mechanical engineering, electrical engineering, and robotics.

application cycles. These data include demographics; academic preparedness, such as SAT scores and high school GPA; and students' most likely field of study. To track students through college, we merged the application data with administrative enrollment records from the National Student Clearinghouse. The NSC file provides the school identifier of the institution where each student is enrolled each term, as well as the student's major(s), if any have been declared.

Finally, we conducted a survey of the applicant sample to elicit outcome measures not typically captured in administrative records. We asked students about their current academic status, the components of their financial aid packages, career confidence, employment status, financial security, social connectedness, and academic engagement. Section 4.4 provides additional detail about the survey design and methodology.

4.2. *Applicant sample*

Table 1 summarizes key characteristics of the AFE applicant sample. Consistent with the AFE program's eligibility criteria, almost three-fourths of students report computer science or computer engineering as their primary interest for post-secondary study (Column 1). Over two-fifths of applicants come from low-income families, defined as those with a Student Parent Contribution (SPC) below $5,000 a year. SPC is a Scholarship America proprietary financial need measure that takes a wider group of assets and debts into consideration than the Federal Student Aid Form. Nearly a third of applicants report being the first in their family to attend college ("First-generation").

The AFE program is highly competitive, with only 4.6 percent of applicants receiving awards. The average applicant has a high school GPA of 3.8, well above the minimum 2.5 required, and scored in the 80th percentile on their SATs. Columns (2) and (3) report sample means separately for recipients and non-recipients. The average AFE recipient has a high school GPA of 3.93. Across the three application cohorts we study, a total of 848 students received an AFE scholarship.[3]

[3] We drop a small number of applicants whose application records did not contain complete demographic information, including four recipients.

Table 1: Applicant sample

	All Applicants (1)	Recipients (2)	Non-recipients (3)
% Received Award	4.58	100	0
Demographics (%)			
Low-income	43.9	82.7	42.1
First-generation	32.9	51.5	32.0
Academics			
SAT Math	682	731	680
SAT Reading	658	700	656
GPA	3.80	3.93	3.80
Expected Majors (%)			
Computer Science	61.5	66.4	61.2
Computer Engineering	11.6	11.7	11.6
Other Engineering	12.6	7.1	12.9
Other	14.3	14.9	14.3
N	18,516	848	17,668

Notes: This table describes characteristics of students who applied to the AFE scholarship program in the four application cycles between 2020 and 2023. Column (2) restricts the sample to applicants who received an award, and Column (3) restricts to non-recipients.

4.3. *Survey*

We administered a survey in late November 2023 to collect additional student outcomes. We constructed it based on established surveys of early-stage college students, including the Beginning Postsecondary Students Longitudinal Study and the National Postsecondary Student Aid Study (both conducted by the National Center for Education Services), as well as previous surveys of award recipients conducted by Amazon. Both recipients and non-recipients were surveyed to allow for treatment comparisons. To minimize the potential for responses to be biased by recipients' relationship with Amazon, survey invites were sent from Scholarship America, and no mention was made of the survey's connection with Amazon. Each student who completed the survey received a $15 Amazon gift card code.

The survey was distributed in two waves in order to manage the total expenditure on survey incentives. The first wave was distributed via text message and included all recipients and non-recipients with application scores in a competitive range.[4] Applicants with competitive scores were prioritized in order to maximize the sample size available for the cutoff-based research design. The second wave was distributed to all applicants, regardless of application score, via email. This broader survey was conducted to gather information on non-competitive applicants and as a second attempt to reach applicants included in the first wave by using a different channel

[4]Specifically, applicants were included in the first wave if their application score fell within 20 points of the cutoff score (on a 100 point scoring scale).

of communication.

In total, 1,565 applicants responded to the surveys,representing 8.5 percent of the full sample. Among recipients, the response rate was 34 percent, compared with 16 percent for competitive non-recipients and just 7 percent for non-recipients overall. The reason for the difference in response rates is unclear, but may be due to recipients having regular communication and familiarity with Scholarship America from the time they receive the award.

The sharply different response rates of recipients and non-recipients raise the concern of sample bias. Table 2 evaluates how representative survey respondents are of the full applicant pool. On a range of demographic and academic characteristics, survey respondents resemble the full applicant pool fairly closely. Columns (2) and (3) report on the same comparisons among the sample of recipients and non-recipients, respectively. Again, the survey samples appear fairly representative across each of the reported characteristics.

Table 2: Survey sample

	Applicants		Recipients		Non-recipients	
	All	Survey	All	Survey	All	Survey
	(1)	(2)	(3)	(4)	(5)	(6)
Response rate		8.5		34.2		7.2
Email		6.9		19.6		6.2
Text		1.6		14.6		1.0
Demographics						
Low-income	43.9	51.2	82.7	80.3	42.1	44.6
First-generation	32.9	37.3	51.5	47.2	32.0	35.1
Academics						
SAT Math	682	711	731	737	680	705
SAT Reading	658	686	700	708	656	681
GPA	3.80	3.87	3.93	3.94	3.80	3.86
N	18,516	1,565	848	290	17,668	1,275

Notes: This table compares characteristics of the full applicant sample (Column 1) with the characteristics of students who responded to our survey (Column 2). Columns (3) and (4) report the analogous statistics for scholarship recipients, while Columns (5) and (6) report on non-recipients.

5. Methodology

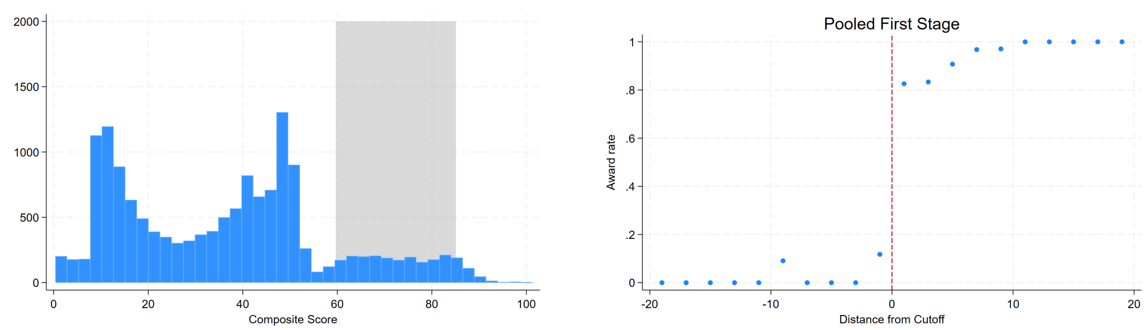
To measure the causal effects of AFE awards, we leverage variation in award assignment stemming from cutoffs used by Scholarship America. Composite scores provide one-dimensional summaries of applicant competitiveness. Applicants with the best composite score ranks were awarded scholarships until no awards remained. Importantly, the cutoff rank is predetermined by the number of funded awards, and applicants have no way of anticipating the cutoff score or how their application will be scored relative to the cutoff. Whether an applicant falls just above or just below the cutoff is therefore plausibly due to chance. This analysis will compare the outcomes of students who just clear award qualification thresholds with those of students who fall just short.

The validity of this approach, known as a regression discontinuity design (RDD), rests on the assumption that student characteristics vary continuously near the cutoff rank, allowing for an "apples-to-apples" comparison of outcomes for students at the margin. Panel (a) of Figure 3 plots the distribution of application scores across all four application cohorts. The score in each application cycle is standardized to lie on a scale between 0 and 100, with 100 being a perfect application. We infer the value of the cutoff in each application cycle as the first percentile application score among scholarship recipients. The gray-shaded region marks the range of the scoring scale where cutoffs fall in our sample. As the figure illustrates, the distribution of composite scores is near-uniform in the relatively high scoring region where score cutoffs lie.

Panel (b) of Figure 3 confirms that award assignment indeed conforms to a cutoff-based selection system. Binning applications by the distance of their assigned score from the cutoff score shows that essentially all applicants with scores exceeding the cutoff are awarded an AFE scholarship (points to the right of the vertical dotted line). Conversely, applicants with scores below the cutoff very rarely receive a scholarship. This discontinuity in the probability of award receipt as a function of the application score underpins our regression discontinuity approach.

Figure 1: AFE scholarship program scoring and selections

(a) Distribution of application scores (b) Award rate by application score



Notes: Panel (a) plots the frequency of application scores across the four application cycles in the sample, where scores in each cycle are normalized to take values from 0 to 100. Panel (b) plots the likelihood of scholarship receipt as a function of distance from the cutoff score. Each point represents the share of students in a given distance bin who received a scholarship.

Our analysis visualizes the discontinuity in outcomes at the cutoff using mean-bin scatter plots, as in Figure 3 Panel (b). To present point estimates more systematically, and to test for statistical significance, we also implement our RDD using a linear specification estimated using ordinary least squares (OLS). In particular, we approximate the conditional expectation of the outcome of interest as a function of the running variable (the application composite score) using a linear trend, but allowing for a discontinuity at the cutoff score.

The causal effect of interest is linked to the size of this discontinuity, given by the parameter ρ in the following equation:

$$Y_i = \rho A_i + \gamma' X_i + \sum_{t \in \{2020,2024\}} \beta_t s_i + \alpha + \varepsilon_i. \tag{1}$$

Here, A_i indicates award receipt, X_i is a vector of demographic controls, and s_i is the distance of the application's assigned score from the cutoff score i. However, as shown by Panel (b) of Figure 1, a small share of award determinations are not explained by the score cutoffs we infer. To account for this, we instrument for A_i in Equation (1) using an indicator for whether the application's score cleared the cutoff. Specifically, we model award receipt as

$$A_i = \pi T_i + \delta' X_i + \sum_{t \in \{2020,2024\}} \lambda_t s_i + \mu + \nu_i, \tag{2}$$

where $T_i = 1[s_i \geq 0]$ indicates having a cutoff-exceeding score. This approach, known as a "fuzzy" RD, appropriately adjusts the magnitude of discontinuities in outcomes across the cutoff to recover the causal effect of receiving a scholarship.

We estimate this system of equations using two-stage least squares (2SLS) and report 2SLS estimates of ρ as our RD estimate of the causal impact of AFE awards. We also restrict the sample used for RD estimation to applications with scores that fall within ± 10 percentage points of the cutoff to further isolate variation in outcomes attributable to award cutoffs.

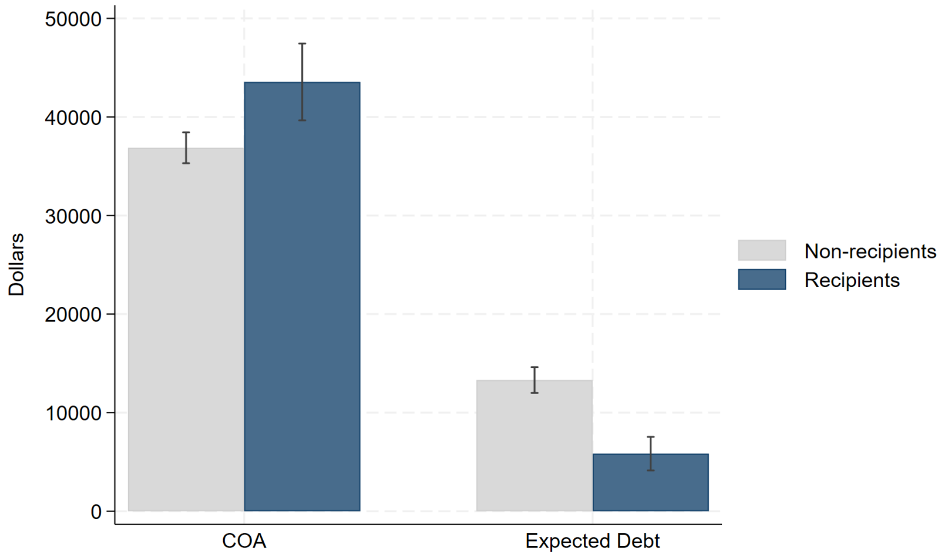
6. Effects of the AFE Scholarship Program

6.1. *A first look at financial aid*

Before turning to the cutoff-based design for measuring causal effects, we first present some descriptive comparisons between the college costs faced by AFE recipients and non-recipients, and the portion of these costs covered by various sources of financial aid. These comparisons do not necessarily indicate the effectiveness of the AFE program because they fail to capture unobserved differences between students who do and do not receive an award, but provide a first look at the financial burdens borne by students in our sample.

We asked students to estimate the cost of attendance (COA) and the debt they expect to incur for the year they were surveyed. COA includes tuition, room and board, meals, books and materials, and other fees associated with enrollment. As shown in Figure 1, recipients report attending institutions with slightly higher COA than non-recipients. Despite attending more expensive schools, they report less than half the debt burden While non-recipients anticipate taking on more than \$12,000 of debt, recipients bear less than \$6,000 in debt.

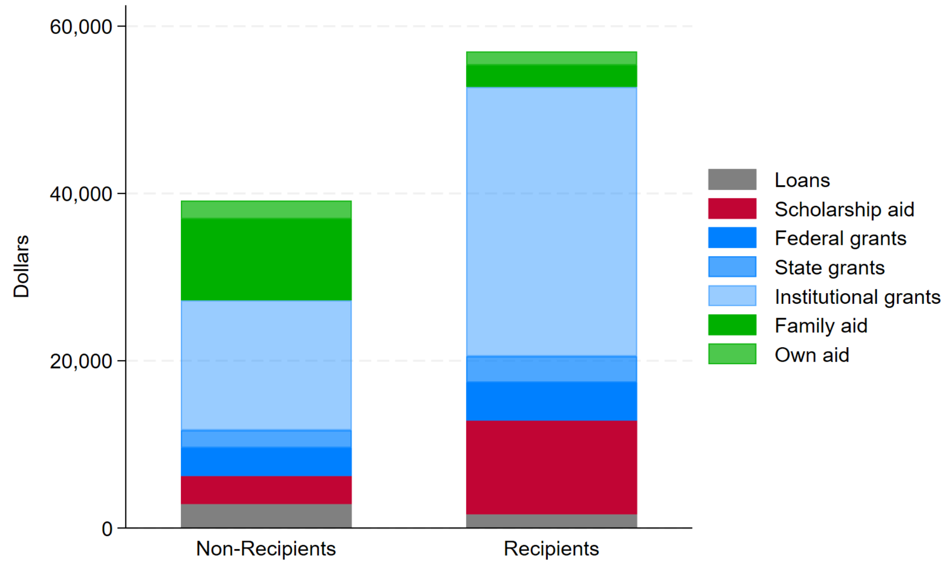
Figure 2: Average college cost of attendance (COA) and expected debt



Notes: This figure plots average cost of attendance (COA) and reported expected debt for the current school year among surveyed students, split by recipients (dark blue) and non-recipients (gray). COA includes tuition, room, board, and other enrollment-related fees and expenses.

Our survey also asked students to estimate a breakdown of their funding sources. As show in Figure 2, AFE recipients report significantly higher institutional grant aid, perhaps indicative of differences in the types of colleges attended, and consistent with their higher average COA. They also report receiving more aid from external scholarships. Recipients rely less on loans and family or personal savings. While non-recipients receive an average of \$3,355 in total external scholarship aid, AFE recipients receive an average of \$11,138 (which includes the \$10,000 from the AFE award).

Figure 3: Average financial aid packages



Notes: This figure shows the (self-reported) contribution of seven types of financial aid toward covering students' cost of attendance. Students who were unsure about how much financial aid they received of any given type were asked to provide their best guess.

The stark differences in the average financial aid packages of recipients and non-recipients suggest that the AFE program makes college more affordable. AFE applicants overall appear to target and attend fairly expensive institutions, with average COA north of $35,000 a year, and finance a substantial share of total cost through personal savings and student loans. Recipients of the AFE program report lower unmet need, with a greater share of costs covered by scholarship aid; non-recipients do not recoup the lost aid through other scholarship opportunities.

6.2. *Effects on financial aid*

We first examine the causal effects of AFE award receipt on students' financial aid packages, again relying on survey responses. Unlike the analysis in Section 6.1, however, we now focus on applicants with composite scores close to the cutoff using the regression discontinuity methodology outlined in Section 5.

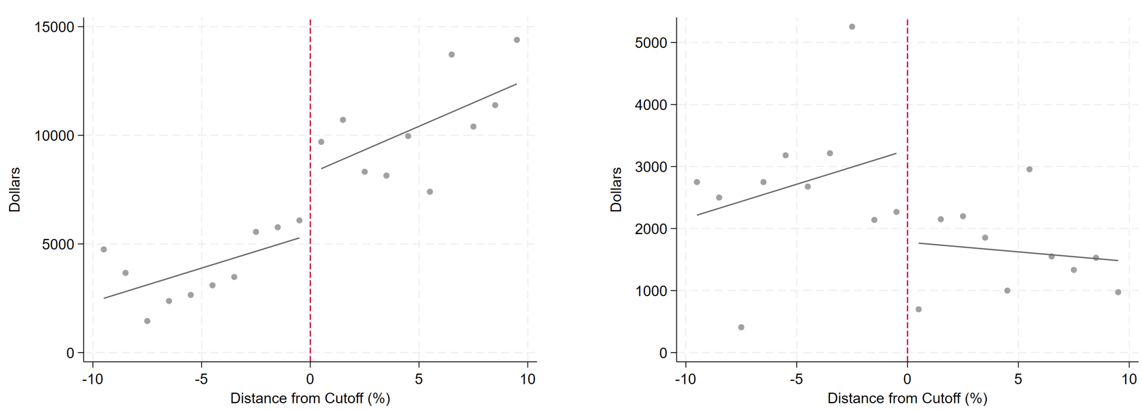
Figure 4 evaluates how receiving an AFE award affects three measures of financial aid. Panel (a) plots average total scholarship dollars received across different bins of the composite score. The cutoff score, marked by the dotted red line, is again normalized to zero, allowing data to be pooled across application cycles with different cutoff values. To the left of this red line are applicants with scores just below the cutoff value, the vast majority of whom did not receive an AFE award (as previously shown in Figure 1, Panel b). Non-recipients with scores closest to the cutoff report obtaining around $5,000 in aid from other sources. To the right of the red line are applicants with scores just above the cutoff. These students report receiving nearly double the total amount of scholarship aid.

This finding qualitatively aligns with the descriptive comparisons in Section 5, though the difference in scholarship aid is slightly lower among applicants close to the cutoff than when comparing raw means drawn from the full applicant pool. As shown in Panel (a), students with higher scoring applications tend to receive more scholarship aid. The RD analysis reveals that students who are competitive for an AFE award but do not receive one find scholarship funding from other sources. Still, and unsurprisingly given the size of the award, the AFE program has a substantial positive effect on total scholarship aid.

Panel (b) of Figure 4 uses the RD analysis to examine the causal effect of AFE awards on average reported student loans. While this outcome is noisier than for scholarship aid, average loans appear to drop significantly at the cutoff score. Non-recipients near the cutoff report taking out around $3,000 in annual loans, while recipients just above the cutoff take out an average of around $2,000 in loans.

Figure 4: Financial aid effects

(a) Scholarship aid (b) Loans



Notes: This figure visualizes the regression discontinuity design by plotting the binned means of two outcomes—scholarship aid in Panel (a) and loans in Panel (b)—as a function of an applicant's distance from the cutoff score. The sample for both figures consists of survey respondents, detailed in Table 2.

Table 3 presents point estimates underlying the visual discontinuities in binned means shown in Figure 4 using OLS regression. For reference, Column (1) reports the non-recipient mean for each of the outcome variables in the row headings. Column (2) reports the difference in outcomes between recipients and non-recipients, with regression adjustment for a number of important applicant traits, including demographic characteristics, baseline academic achievement, and the year of application. Consistent with the descriptive analysis in Section 6.1, recipients and non-recipients exhibit large differences in aid receipt and debt burdens. Column (2) shows that these disparities remain even after accounting for differences in observable characteristics between the two groups.

To account for unobservable differences between recipients and non-recipients, we turn to the regression discontinuity design. Column (3) reports treatment effect estimates from OLS estimation of Equation 1, which implements the RDD. To isolate variation in outcomes attributable to the score cutoff, and consistent with the visual representation in Figure 4, we keep only students who scored within 10 percentage points (on a standardized 100-point scale) of the cutoff. To implement the RDD, we additionally control for the composite score.

Using the RDD approach, we estimate that the AFE program increases scholarship aid by nearly $3,700, as seen in the first row of Column (3). The positive effect on scholarship aid reported here does not appear to be offset by a reduction in other grant aid (i.e. , federal, state, or institutional aid). This implies that the AFE scholarship substantially increases the total grant aid students receive. However, the RD estimate of $3,700 is substantially smaller than the non-causal treatment-control comparison reported in Column (2). Again, this discrepancy is due to non-random selection of applicants into award receipt; applicants selected to receive an AFE award would have received more aid than non-recipients, even in a world without AFE support.

We estimate sensible negative effects on sources of aid we expect AFE awards may displace, though we lack the statistical power in the survey sample necessary to achieve conventional levels of statistical significance. Directionally, however, the point estimates indicate the program reduces reliance on self-financing and loans, in line with Figure 4. Column (5) reports RD estimates for low-income respondents. Though the sample size is smaller in this column, we estimate that the AFE program increases scholarship aid and lowers debt by similar magnitudes as in the full sample.

As shown in Panel (b) of Table 3, we find no definitive indication that AFE awards significantly influence the types of colleges students choose to attend. Applicants in general attend schools that are selective, with an average admissions rate of 51 percent. The estimates suggest that awards may push lower-income students toward slightly more expensive and selective schools, but the effect is small and imprecise. Overall, these minimal effects on enrollment patterns are consistent with the baseline competitiveness and ambition of the students in the AFE applicant pool.

Table 3: Financial aid effects

	All Respondents			Low-income Respondents	
	Non-recipient Mean (1)	Demographic controls (2)	Regression Discontinuity (3)	Non-recipient Mean (4)	Regression Discontinuity (5)
Panel A. Financial Aid					
Scholarship aid	3,355	7217.8***	3676.6*	3,373	3246.5+
	[5,913]	(429.5)	(1655.2)	[5,802]	(1933.4)
Other grant aid	20,996	12744.2***	1798.3	25,667	8862.1
	[23,046]	(1674.9)	(6904.0)	[24,658]	(8288.8)
Self finance	9,722	-4769.0***	-2782.0	4,748	-3103.0
	[15,045]	(919.3)	(2405.1)	[10,823]	(2291.6)
Loans	2,873	-1057.6**	-1707.7	2,664	-1305.1
	[5,462]	(377.7)	(1208.5)	[5,085]	(1293.4)
Debt	13,307	-6424.2***	-7043.9+	10,312	-5611.5
	[23,073]	(1555.0)	(4061.3)	[19,052]	(4073.8)
N	1,196	1,478	390	534	290
Panel B. Institution Characteristics					
4-year	0.78	0.0172	-0.0372	0.77	-0.0629
	[0.42]	(0.015)	(0.051)	[0.42]	(0.061)
Tuition	19,029	9479.6***	1280.4	18,333	5154.1
	[17,654]	(673.8)	(2720.3)	[17,588]	(3247.1)
Admissions rate	0.51	-0.123***	0.0133	0.53	-0.0253
	[0.25]	(0.009)	(0.033)	[0.24]	(0.039)
N	17,646	18,489	1,775	7,409	1,208

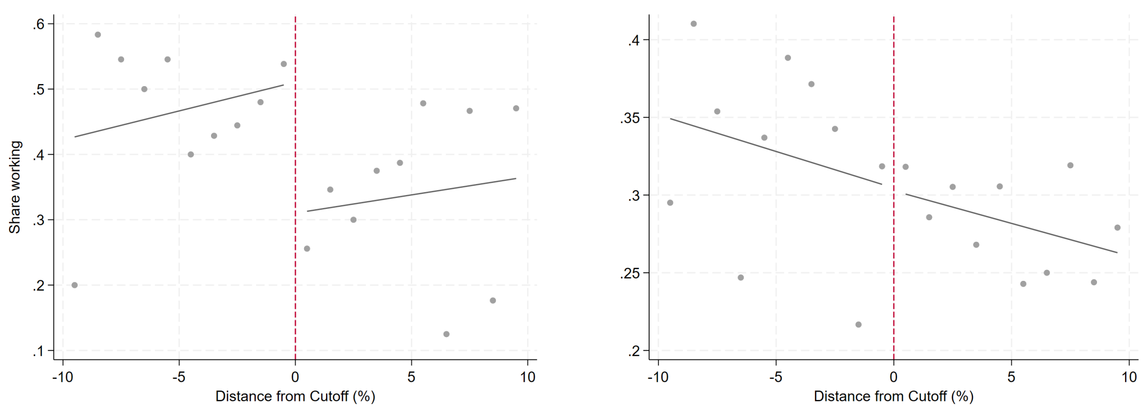
Notes: (+ $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$) This table presents effects estimated using our regression discontinuity design (described in Section 5) for a range of financial aid components. For context, in Column 1 we report the non-recipient mean for each outcome and in Column 2, the difference in aid received between recipients and non-recipients, regression-adjusted for a set of demographic controls. The RD estimate of award impact is reported in Column 3. The sample in Column 3 restricts to applicants with a score within 10 points (on a 100-point scale) of the cutoff score. Demographic controls (common to columns 2 and 3) include gender, four race categories, high school GPA, first-generation status, and standardized test scores. Columns 4 and 5 restrict the sample to students with a suggested parent contribution of less than $5,000.

6.3. ***Effects on work and academic engagement***

We next turn to evaluating how the AFE awards affect recipients' on-campus lives. Panel (a) of Figure 5 visualizes the regression discontinuity in the likelihood of working while in school. Almost half of competitive non-recipient applicants report working at least part-time while enrolled. However, the probability of working drops nearly 20 percentage points to the right of the cutoff score, pointing to a sizable causal reduction in work. Panel (b) examines the likelihood that students have declared a computer science or related major in their first year in college. Here, we find no observable jump at the discontinuity, suggesting little aggregate effect on first-year CS declaration.

Figure 5: Effects on work and academic engagement

(a) Working in school (b) Declaring a CS major in first year



Notes: This figure plots binned means for outcomes related to academic engagement as a function of an applicant's distance from the cutoff score. Students are considered working in Panel (a) if they reported being employed at least part-time while enrolled in school. The sample for both figures consists of survey respondents, detailed in Table 2.

Table 4 investigates these effects in further detail. Using our RDD regression specification, we estimate that AFE awards lower the probability of working while in school by 28 percentage points. Corroborating the visual evidence from Figure 5, we find no meaningful effect on first-year CS declaration in aggregate.

One reason for this null result may be that few institutions require or encourage students to declare majors in their first year. As a supplemental outcome, our survey asked students what major they currently *intend* to pursue. As shown in the third row of Table 4, award recipients are 21 percentage points more likely to express interest in computer science or related fields.

The last two rows in Table 4 investigate effects on financial stability and peer connectedness. We construct indices for both outcomes that pool categorical responses from multiple survey questions. The financial stability index sums responses from questions asking how much students worry about affording room and board and managing their college debt. The peer connectedness index pools responses from questions about whether students feel they know peers in their field of study at their own school and at other schools, and whether they can rely on these connections to learn about professional opportunities. To facilitate interpretation of magnitudes, we normalize each index by the standard deviation of the distribution of values among non-recipients.

We find that the AFE program has positive effects on both financial stability and peer connectedness as measured by the constructed indices. Both effects are quite large, with magnitudes of around half a standard deviation. The observed improvement in financial stability is in line with previous work examining how aid helps students manage incidental costs. Meanwhile, the AFE program's extensive wraparound services bring scholarship recipients together. Both financial stability and social connectedness may help students better navigate their academic course loads and take advantage of professional opportunities.

Table 4: Effects on work and academic engagement

	All Respondents			Low-income Respondents	
	Non-recipient Mean (1)	Demographic controls (2)	Regression Discontinuity (3)	Non-recipient Mean (4)	Regression Discontinuity (5)
Currently working	0.46	-0.0844*	-0.283*	0.46	-0.327*
	[0.50]	(0.035)	(0.121)	[0.50]	(0.142)
First-year CS major (NSC)	0.38	-0.0289+	0.0265	0.38	-0.0492
	[0.48]	(0.017)	(0.061)	[0.49]	(0.071)
Intend to complete CS major	0.72	0.146***	0.213*	0.72	0.247*
	[0.45]	(0.031)	(0.100)	[0.45]	(0.115)
Financial stability index	(1.48)	0.201***	0.416+	(1.59)	0.414
	[1.00]	(0.069)	(0.236)	[1.00]	(0.269)
Peer connectedness index	2.86	0.303***	0.556*	2.71	0.462
	[1.00]	(0.071)	(0.254)	[1.00]	(0.304)
N	1,196	1,478	390	534	290

Notes: (+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001) This table reports effects estimated using our regression discontinuity design (described in Section 5) for a range of outcomes related to academic engagement. For context, we first report the non-recipient mean for each outcome in Column 1, along with the difference in outcomes between recipients and non-recipients regression-adjusted for a set of demographic controls (Column 2). The RD estimate of award impact is reported in Column 3. The sample in the RD specification in Column 3 restricts to applicants with a score within 10 points (on a 100-point scale) of the cutoff score. Demographic controls (common to columns 2 and 3) include gender, four race categories, high school GPA, first-generation status, and standardized test scores. Columns 4 and 5 restrict the sample to students with an annual suggested parent contribution of less than $5,000.

6.4. *Effects on internships and career plans*

Finally, we examine how AFE awards affect students' confidence in obtaining and completing internships and in finding work in their chosen professions. Table 6 reports our findings. Column 3 shows small positive effects on confidence both in finding an internship and in finding a desirable job. [5]

The last section of our survey asked students whether they plan to complete an internship in the upcoming summer, as well as whether they have already completed an internship. We find large positive effects for both outcomes. While 68 percent of non-recipients reported having internship plans, we estimate AFE awards increase this share by an additional 24-percentage points. The point estimate for low-income students is also positive, though much smaller in magnitude. Estimates for internship completion are slightly noisier, since much of the sample is still in the first

[5] Students were asked to select from the following responses to questions about confidence in finding internships and jobs: "Completely confident", "Fairly confident", "Somewhat confident", "Slightly confident", "Not confident at all." These responses were subsequently coded into a numeric 5-point scale.

or second year of college; that said, we estimate a positive and marginally significant, impact of 13 percentage points.

Table 5: Effects on internship and career plans

	All Respondents			Low-income Respondents	
	Non-recipient Mean	Demographic controls	Regression Discontinuity	Non-recipient Mean	Regression Discontinuity
	(1)	(2)	(3)	(4)	(5)
Confident will find internship	2.86	0.275***	0.365	2.82	0.389
	[1.07]	(0.076)	(0.256)	[1.11]	(0.313)
Confident will find job	3.06	0.121+	0.0198	2.99	-0.0787
	[0.94]	(0.067)	(0.232)	[0.98]	(0.285)
Plan to complete internship	0.68	0.201***	0.237**	0.67	0.194+
	[0.47]	(0.030)	(0.091)	[0.47]	(0.106)
Completed internship	0.36	0.102***	0.134+	0.31	0.173+
	[0.48]	(0.028)	(0.080)	[0.46]	(0.096)
N	1,196	1,478	390	534	290

Notes: (+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001) This table reports effects estimated using our regression discontinuity design (described in Section 5) for outcomes related to career planning. For context, we first report the non-recipient mean for each outcome in Column 1, along with the difference in in responses between recipients and non-recipients regression-adjusted for a set of demographic controls (Column 2). Confidence is reported on a 5-point scale, with a value of 1 being "Not confident at all" and a value of 5 being "Completely confident." The RD estimate of award impact is reported in Column 3. The sample in the RD specification in Column 3 restricts to applicants with a score within 10 points (on a 100-point scale) of the cutoff score. Demographic controls (common to columns 2 and 3) include gender, four race categories, high school GPA, first-generation status, and standardized test scores. Columns 4 and 5 restrict the sample to students with a suggested parent contribution of less than $5,000.

7. Conclusion

This report contributes to the growing literature on the causal effects of scholarship aid by evaluating the impact of a large-scale scholarship program designed to encourage engagement and persistence in computer science. The Amazon Future Engineer Scholarship program combines financial and professional supports, including a guaranteed internship at Amazon. Using a regression discontinuity design based on score assignment cutoffs, we find substantial reductions in unmet financial need and the likelihood of working while in school. Awards boost the probability that students pursue and complete internships.

Our findings point to the promise of combining financial awards with opportunities for students to form connections with peers and mentors and to gain pre-professional experience—boosting their career prospects. As the demands of entry-level employment in software engineering and other technical fields become more stringent, increased internship opportunities may play a key role in promoting diverse work forces. Our sample extends only back to 2020, limiting our ability to measure impacts on longer-run outcomes. Still, the AFE program appears to have a substantial impact on surveyed intention to pursue a degree in CS. A small but growing number of AFE recipients are also transitioning to full-time employment at Amazon after successful summer internships, a trend we expect to continue. In future follow-up evaluations of AFE recipients, we hope to have a clearer statistical picture of how AFE awards increase persistence in CS majors and degree attainment.

While some aspects of the AFE program are specific to Amazon, several of our findings may be applicable to the design and administration of scholarship programs more broadly. Our results corroborate a growing body of evidence that scholarship awards are particular beneficial to groups that have not traditionally benefited from aid exclusively awarded on the basis of academic merit, including low-income students (Angrist et al. 2022). Given the mounting evidence of outsize award impacts for these students, scholarship programs may be able to increase their aggregate impact by weighing financial need more heavily than traditional measures of merit in their application process.

At the same time, we emphasize that the impacts of the AFE program may not generalize to award programs that are primarily financial, offer a very different bundle of supports, or operate in different industries. We encourage scholarship providers to consider measuring the impact of their own programs. In ongoing work, we are also collaborating to evaluate the impacts of Scholarship America's programs at large using the regression discontinuity methodology employed here, in view of shedding light on what factors may make some scholarship programs especially impactful.

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